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Global warming, grain production and its efficiency: Case study of major grain production region

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ABSTRACT

Historical records and multiple researches have indicated that there is a close connection between carbon dioxide and surface temperature. Climate change and its impacts on agriculture, especially grain production, is one of the major challenges for food security and sustainable development. From the perspective of natural flow, climate change directly affects plant growth via water circulation, such as droughts and floods. Although the covariation of surface temperature and CO_2 concentration will to some extent benefit crop photosynthesis, grain production may fluctuate according to the grain market, which is also affected by its erratic provisioning. We then determine how climate change affects grain production and efficiency using an input distance function and technical inefficiency model. First, we discover a significant relationship between surface temperature and grain production, although this impact is marginal; the coefficient is 0.0037 in the estimated model. Second, we find that surface temperature influences grain production not only through its photosynthesis but also its production efficiency in major grain production areas. And grain production efficiency is in a decreasing trend from 2000 to 2010, the average efficiency in 2010 is 0.75 on the whole. Third, there is a large gap in grain production efficiency among counties in Inner Mongolia, Hebei, Heilongjiang and Henan provinces, according to a distribution map of that efficiency.

1. Introduction

There are mounting evidences that current changes in climate transform the planet's ecosystems, threatening human wellbeing of current and future generations (Gerber et al., 2013). Historical records indicate that global average surface temperature has increased by 1.19 °C since 1880, mainly driven by greenhouse gas from human activity. Most of the warming has occurred over the past 35 years, and current warming trend is of particular importance (Data source: NASA's Goddard Institute for Space Studies). Scientists have become more confident that many unprecedented changes observed over decades to millennia are mainly caused by climate change. Examples include the melting of glaciers leading to sea level rise, extreme weather events disrupting the water cycle, and disturbance of ecosystem functions.

Ecosystem services are components of nature and include products and services provided by diverse ecosystems, such as food, water, timber and so on. Climate change affects ecosystems in a variety of ways. For instance, warming may force species altitudinal shifts, influence water delivery which is critical to plant growth, and even damage habitat biodiversity (Shaw et al., 2011). In coupled these changes with changes in precipitation and an increased frequency of extreme events, agriculture is highly sensitive to climate change and the effects of climate change on agroecosystems have drawn considerable research attention (Ramankutty et al., 2002). As reports from related studies have highlighted that, the suitability of habitat and the amount of irrigation and fertilization for a specific crop are all confounded by the warming temperature and the changing precipitation distribution. However, feedbacks of agroecosystems to climate change vary with region. Here, agroecosystems contain polycultures, monocultures, and mixed systems, comprising crop-livestock systems, agroforestry, agro-silvo-pastoral systems, aquaculture, rangelands, pastures and fallow lands (Fuhrer, 2003). But sensitivity of many of the types of agroecosystems listed above hasn't been studied in detail. Specifically, Peng et al. (2004) indicated that rice yields declined with higher night temperature from global warming by using simulation models, but the mechanism that caused the observed reduction in rice yield was still poorly understood. Our study is mainly focused on cropping systems and the warming temperature.

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From perspective of natural flow, climate change poses challenges to food security and sustainable development of agriculture by affecting the surrounding environment of crops, e.g., soil conditions and availability of water resources. These impacts also in turn affect adaptive policies and food market. With regard to global warming and climatic variability, Trnka et al. (2014) stated that global warming acted on temperature and precipitation, and these meteorological variables were all critical natural conditions for crop growth. But the impacts of warming on agriculture remained uncertain. Lobell and Field (2007) indicated that warming was conducive to crop yield in some areas, but inhibitory or of little consequence in others. As field studies have shown, greenhouse gas may have profound effects on grain productivity, through both the increase of average surface temperature and amount of CO_2 available for photosynthesis (Vaghefi et al., 2011). Sheehy et al. (2006) indicated that the interaction of changes in CO_2 and temperature determined grain production and that increasing CO_2 concentration affected plant growth, but its net effects depended on temperature increase. Asseng et al. (2015) held a view that rising temperature would reduce global wheat production via sowing data simulation. Then, warming has an advantage for agriculture development via prolonging growth season of partial crops, but it also exerts pressures on grain production via altering environmental conditions or causing natural resource issues (water cycle, soil conditions, etc). Thus, on one hand, the interaction between temperature and grain production cannot be identified because of heterogeneities of natural conditions in different regions. On the other hand, it is uncertain whether the benefits of grain production from warming weigh over the loss caused by environmental change and natural resource pressures.

Aside from the disturbance of global warming on habitat of plant growth, adaptive efforts on agriculture adopted by government and farmers in response to the rising temperature to some extent affect grain production. Then with the support of institutional frameworks, agricultural technologies, policies and guidance from farmers, communities and local governments, the positive effects of global warming may occur (Peng et al., 2004). As the investigation conducted by Yang et al. (2007) have reported, Jilin and Liaoning province are able to grow rice with the warming, which is also one of the reasons for the expansion of rice planting areas. In addition, a high proportion of farmers have taken advantage of changing conditions by planting calendar and adjusting planting techniques to enhance their farming production. As the research from Le Dang et al. (2014) have indicated, the spring wheat sowing date was shifted from the beginning of May to the end of March with warming after 1990 in Changtu County in Liaoning province. Therefore, farmers or government adaptions in respond to global warming affects grain production.

Our research is intend to explore interactions between climatic variability and grain production in a major grain production region, and to ascertain effective means for agroecosystems to adapt to climate change. First, we select vital input variables for grain production to construct an input distance function to detect how climate change affects grain production. Second, a technical inefficiency model is used to determine inefficiency factors in grain production. Third, adaptive measures are proposed based on model simulation results.

2. Study area

We have explored how climate change influenced agriculture, especially grain production and its efficiency. Then, a major grain production area in China has been selected as a case study to ascertain their relationships. Owing to suitable geographic, soil, climate and technical conditions for crop breeding, the aforementioned area is across multiple regions and mainly located in the Northeast China Plain, Central China and Middle Eastern part of our nation (Fig. 1). The total land area is 3.59 million km^2 (2014) extending across the Inner Mongolia Autonomous Region and Hebei, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hunan and Sichuan provinces. Total grain acreage in these provinces is 0.767 million ha (2014), accounting for 68.04% of the national figure. Total grain output was 434.37 million tons in 2014, accounting for 71.55% of our national output. Because of differences of annual temperature, precipitation, soil type and climate change, the crop structure varies by region.

As a basic sector, agriculture is heavily reliant on environmental conditions (Peltonen-Sainio et al., 2016). Due to the monsoon climate at midlatitudes, precipitation in China decreases from the east and southeast to west and northwest (China Meteorological Data Service Center, http://data.cma.cn/en). Limited by the natural conditions, the grain output from eastern provinces, especially the Northeast China Plain exceeds that of those from the west. In 2014, because of intensive breeding, mechanized farming and effective management, and fertile soil, Heilongjiang Province had the largest grain output of any provinces, reaching 62.42 million tons. The second largest grain production region was Henan Province, whose wheat output constituted 24.4% of the national output. Its total grain output in that year was 57.72 million tons. The third largest grain production was in Shandong, a coastal province with ample sunlight and rainfall, its grain output was 45.97 million tons. Grain output of all regions has risen with time to varying degrees. With technical and economic progress and the impact of climate change, the provinces have implemented different measures to adjust industrial structure and accelerate agricultural development. Combined with environmental and human factors, the gap of grain output among the provinces has expanded (NBSC, 2016). The main crop production area has gradually focused on the Northeast China Plain and Central China, and the crop production center has changed. For example, in 2000, Heilongjiang Province had a total grain output of 25.46 million tons, ranking only seventh among these provinces. After technical and management improvement and under climate influences, Heilongjiang became the largest crop production province in 2014. Its output increased 254.17%. Conversely, output in western provinces such as Inner Mongolia Autonomous Region and Sichuan has slightly changed during the same period. Thus, in the set of climate change, there is much spatial distinction of agricultural production among regions, which should be further explored. Multi-region analysis can be conducted to better understand the relationship between climate change and grain production, so we chose 12 main crop production provinces as the study area. The complexity of the problem is thus better unraveled from both spatial and time scales.

3. Input distance function

Following the theoretical framework of Shephard (1970) and empirical studies from Färe (1994), we have incorporated input set X to produce Y in an input distance function, thereby to identify the relationship between grain production and land surface temperature in major grain production regions and calculate their grain production efficiencies. This can be expressed as

$$S^t = \{(X^t,Y^t): X^t \ can \ produce \ Y^t\} \quad (1)$$

where $X^t = \{x_1^t,x_2^t,...,x_n^t\} \in R_+^N$ is the input vector for grain production in the year of t, and $Y^t = \{y_1^t,y_2^t,...,y_m^t\} \in R_+^N$ is the output vector. This can also be defined as

$$D_i^t = sup\{\lambda: \ (X^t/\lambda,Y^t) \in S^t\} \quad (2)$$

The input distance function treats Y^t as given and adjusts X^t as long as (X^t,Y^t) are technologically optimal. Here, λ represents that the given output is achieved with minimum inputs (X_{min}^t). D_i^t refers to the distance between the observations (X^t) and minimum inputs (X_{min}^t) with a given output. If the observed X^t decreases proportionally (λ), then $D_i^t(X^t,Y^t) \leqslant 1$ and $(X^t,Y^t) \in S^t$. In addition, if $D_i^t(X^t,Y^t) = 1$, then

(X^t,Y^t) is on the boundary or frontier of technology (technological optimal). Thus, for sample i of observations, Eq. (3) can be obtained in light of the above definition of the input distance function.

$$D_i^t(X^t,Y^t,t)exp(v_i-\mu_i) = 1 \tag{3}$$

According to Aigner et al. (1977), we attempt to capture noise using a term v_i, and μ_i is defined as technical inefficiency, which is generally subject to

$$\mu_i \in [0,1]$$

where

$$i.\ i.\ d \quad v_i^t \sim N(\mu_i,\sigma_{it}^2) \quad and\ \mu_i^+ \sim N^+(\mu_i,\sigma_{it}^2)$$

Then, Eq. (3) can be transformed into:

$$ln(D_i^t(X^t,Y^t,t)) = \mu_i - v_i \tag{4}$$

Lovell et al. (1994) proposed that the distance function have a character of mathematically homogeneity, which means that the function should meet the following condition.

$$D_i^t(X^t/x_n,Y^t,t) = D_i^t(X^t,Y^t,t)/x_n \tag{5}$$

Then, Eq. (6) can be generated via Eq. (4), conditional on Eq. (5).

$$-lnx_n = ln(D_i^t(X^t/x_n,Y^t,t)) - \mu_i + v_i \tag{6}$$

In a production function simulating the relationship between land surface temperature and grain production and calculating grain production efficiency, we should consider features of the study area and also try different forms of production functions in the model of Eq. (6) to find an adequate one for the main grain production regions, such as Cobb-Douglas production, translog production functions.

In order to estimate Eq. (6) in a parametric setting, a translog form for the empirical case of n inputs and m outputs can be expressed as (Coelli and Perelman, 2000)

$$\begin{aligned} -ln(x_{Ni}) = {} & \alpha_0 + \sum_{n=1}^{N-1} \alpha_n ln(X_{ni}^*) + \frac{1}{2}\sum_{n=1}^{N-1} \alpha_n'(\ln(X_{ni}^*))^2 \\ & + \sum_{n=1}^{N-1}\sum_{k=1}^{N-1} \alpha_{nk}\ln(X_{ni}^*)\ln(X_{ki}^*) + \sum_{m=1}^{M} \beta_m \ln(Y_{mi}) \\ & + \frac{1}{2}\sum_{m=1}^{M} \beta_m'(\ln(Y_{mi}))^2 + \sum_{m=1}^{M}\sum_{l=1}^{M} \beta_{ml}\ln(Y_{mi})\ln(Y_{li}) + v_i - u_i, \quad i \\ & = 1,2,\ldots,h. \end{aligned} \tag{7}$$

where $n \neq k$ and $m \neq l$, $X_{ni}^* = x_{ni}/x_{Ni}$, i denotes the ith county and h is the number of counties we observed, Y_i refers to grain production in our study.

In computing grain production efficiency, we must determine how this indicator is defined in the input distance function. The original form of stochastic frontier analysis (SFA), which is the approach that includes the input distance function, can be written as

$$Y_i = f(X_i,\beta)exp(v_i-\mu_i) \tag{8}$$

Grain production efficiency denotes that the ratio of the observed output to corresponding potential output given by the production frontier, specified as

$$TE_i = \frac{f(X_i,\beta)exp(v_i-\mu_i)}{f(X_i,\beta)exp(v_i)} = exp(-\mu_i) \tag{9}$$

where TE_i is technical efficiency in theoretical framework of SFA and also represents grain production efficiency empirically. If grain production reaches its peak or is on the frontier, that grain production can be expressed as $f(X_i,\beta)exp(v_i)$ with its technical inefficiency equals to 0.

When we compute technical inefficiency through Eq. (9), the technical inefficiency model can be established based on the results of the model of Eq. (6).

$$\mu_i = \tau_0 + \tau_{ij} * Z_{ij} \tag{10}$$

Here, μ_i acts as dependent variable and Z_{ij} is a vector of explanatory variables associated with inputs in the model of Eq. (6). τ_0 is a constant item in the technical inefficiency model, and τ_{ij} is a vector of unknown parameters to be estimated (Battese and Coelli, 1988, 1995; Battese et al., 1996).

For the simulation of the model of Eq. (10), we can identify factors that may influence grain production by affecting its production efficiency.

4. Dataset

We have used agriculture aggregate panel data of 573 counties in the period 2000 to 2010. All the input variables have been selected based on literature review. Neumann et al. (2010) held the view that agricultural intensification acted as a key to increase crop yield and food supply. Drivers of agricultural intensification have been screened based on 91 published studies, representing grain type, temperature, precipitation and soil fertility as the four crop-growth defining factors. They have also indicated that labor availability, irrigation area and other factors are all related to traditional management of grain production. Shi et al. (2013) listed inputs to grain production to analyze its change, including sown area, fertilizer use, and effective irrigation area. Piao et al. (2010) found that climate factors such as precipitation and temperature influenced water resources in China, thereby altering grain production. Thus, we have screened inputs by considering all these factors, based on recent research. Y_i refers to grain production in our study, x_1 denotes sow area for grain, x_2 is labors for agriculture, x_3 denotes agricultural machinery, x_4 and x_5 represent fertilizer for crop growth and electricity for rural use, respectively, and x_6 is the potential productivity of land calculated based on agricultural ecological zoning.

A part of these observations includes data of one output and five inputs (Y, x_1, x_2, x_3, x_4, x_5), which were from statistical yearbooks of each province. Land potential productivity (x_6) is calculated based on Estimation System of Land Production (ESLP) model (Deng et al., 2017). Another part is meteorological data collected from China Meteorological Data Service Center. Summary statistics for the data used in our study are shown in Table 1.

5. Results

5.1. Relationship between land surface temperature and grain production

As shown in Fig. 2, the grain production varies across the study area, and the production in some counties decreases from 2000 to 2010 (counties in red ellipses). Thus, it is important to identify the drivers of grain production efficiency and the relationship between land surface temperature and that efficiency under global warming, to adapt and improve grain production in major production areas.

Thompson (1975) has stated that most global grain belts are limited at lower latitudes by high summer temperatures, and maximum grain yields are usually in summers with below-average temperatures in a particular area. Higher temperatures are conducive to crop growth but they have a threshold. If land surface temperature is above this threshold, it will be no longer an advantage to crop growth. Thus, we used a quadratic of temperature as a control variable to reflect variation of crop growth with increasing temperature. The relationship between land surface temperature and grain production can be obtained from the result of the model of Eq. (7) (Table 2).

Model 1′ is a stochastic frontier analysis without introduction of climatic factors. Not all the first-order coefficients of inputs have the expected signs, e.g., electricity for rural use (x_5) has been expected to be

positive but in fact negative for grain production. Simultaneously, part of the first-order coefficients of inputs is estimated to be statistically significant between 0% and 10%. Sown area (x_1), agricultural labor (x_2), agricultural machinery (x_3) and fertilizer use (x_4) are all in line with the expectation and perform significantly positive to grain production. From the test results in Table 3, model is improved when climatic factors are incorporated in the model of Eq. (10). The gamma value of model 1′ is slightly larger than that of model 2′. This means that climatic factors are clearly associated with grain production and have marginal effects on production efficiency.

5.2. Grain production efficiency of case study area

After estimating the input distance function, grain production efficiency is estimated by Eq. (10). The average estimated grain production efficiency for all counties is 0.75 in 2010 from Model 2′, implying that the main grain production region can reduce inputs by 25% as a whole to sustain current output. As shown in Fig. 3, the average grain production efficiency in each year has a decreasing trend from 2000 to 2010. This trend is slightly smoother than model 1′ without climatic factors. Thus, those factors, including precipitation, sunshine hours, land surface temperature, relative humidity and wind speed, had a close relationship with grain production efficiency.

We have calculated average grain production efficiency of each county during 2000–2010, and the distribution of this key indicator is shown in Fig. 4. As estimates from model 2′ indicate, > 70% of the counties has an average production efficiency > 0.7. Counties with average efficiency < 0.6 are mainly in Inner Mongolia, Hebei, Heilongjiang and Henan provinces. Inner Mongolia, Hebei, Jilin and Henan provinces have the most counties with production efficiency > 0.9. Thus, there is a large gap of grain production efficiency in Inner Mongolia, Hebei and Henan provinces.

5.3. Covariation of land surface temperature with grain production efficiency

Estimates from the technical inefficiency model based on the results of Model 2′ are listed in Table 4. Here sow area, labors for agriculture, land potential productivity and climatic factors except precipitation are negative to technical inefficiency, and which are deductively positive to grain production efficiency in empirical study. Comparatively, the impacts of climatic factors on grain production efficiency have weighed over the other drivers. Consequently, the most effective measures for improving grain production efficiency in major grain production regions are to expand sown areas, increase agricultural employees, and enhance land potential productivity. Moreover, the rising land surface temperature to some extent benefits grain production efficiency. This matches comparison results from the two distribution maps in Fig. 5. This demonstrates that grain production efficiency is relatively higher in regions with higher land surface temperature. Thus, land surface temperature affects grain production via affecting its efficiency, and rising grain production efficiency is available for climate change adaptation.

In reverse, those elements which are positive to technical inefficiency are negative to grain production efficiency in effect. Thus, saving cost or reducing the input on agricultural machinery, fertilizer use and electricity for rural use is also the way to improve grain production efficiency.

6. Conclusion and discussion

Our research has incorporated climatic variables into the input distance function in an efficiency analysis, to obtain the connections between land surface temperature, grain production and grain production efficiency. Findings of how select factors such as sown area and agricultural labor affecting grain production and its efficiency in the case study area provide practical information to reduce farming costs and enhance grain production. Based on the literature, rising temperature benefits crop growth and raises grain production in certain regions. However, estimates in our study indicate that land surface temperature marginally affects grain production and has positive effects on grain production efficiency, with a *p-value* of the estimated coefficient between 0% and 10%. The simulation matches the finding that grain production efficiency is higher in regions with higher land surface temperatures, from comparison of land surface temperature map and distribution map of grain production efficiency (Fig. 5). Meanwhile, we have found that a large gap of grain production efficiency in Inner Mongolia, Hebei province and Henan province, a great deal of whose counties' grain production efficiency was beneath 0.6 and also have many beyond 0.9. On the whole, average grain production efficiency is 0.75 in the year 2010, and over 70% of the county's efficiency is beyond 0.7. Exploring interaction among land surface temperature, grain production and its efficiency is helpful for improving grain production and provides information for climate change adaptation on agriculture. It suggests that policy maker may adopt measures to expand sown areas, increase agricultural employees and enhance land potential productivity, and also save costs on agricultural machinery, fertilizer use and electricity for rural use.

However, the limitation of our research is obvious that some input variables such as agricultural labors (x_2) doesn't perform well in the model, due to that we take labors in rural areas instead of labors for agriculture production as the input. This is constrained by the data source. On the other hand, adaptive options implemented by farmers, government and non-profitable organizations are also one of the main factors for grain production. But we haven't incorporated related control variables in our model, due to the absence of field survey and the obscure range of adaptations.

Conflict of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix A

See Figs. 1–5 and Tables 1–4.

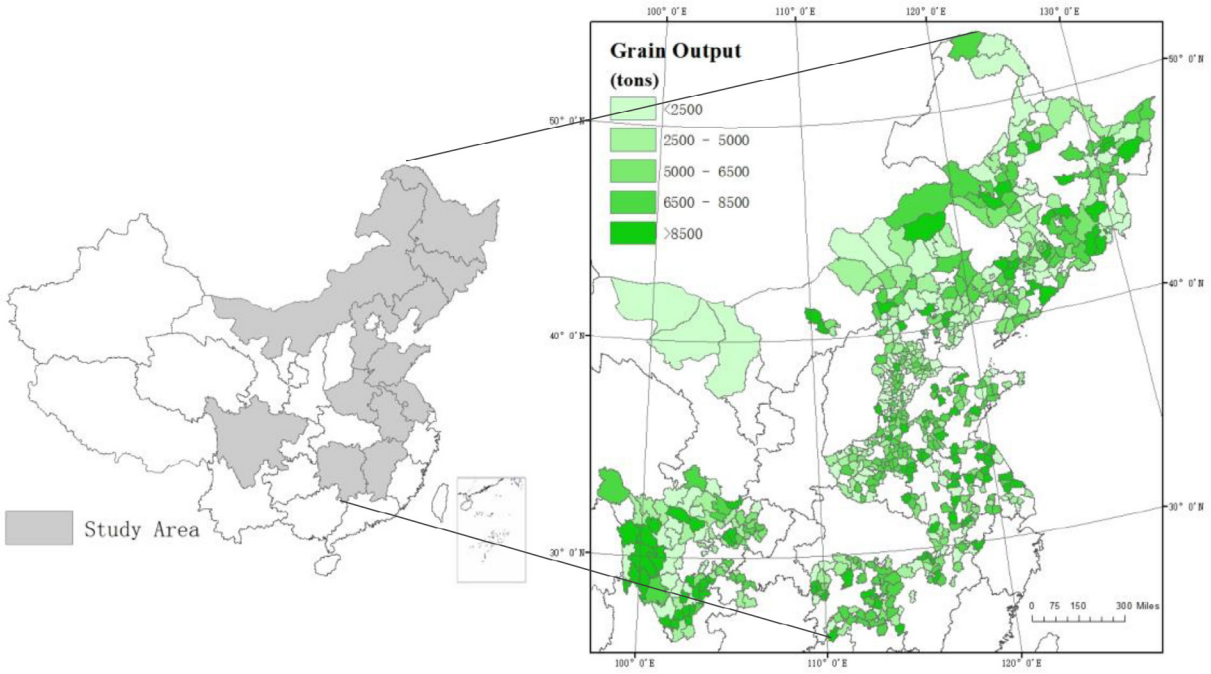

Fig. 1. Geographic location and range of major grain production region.

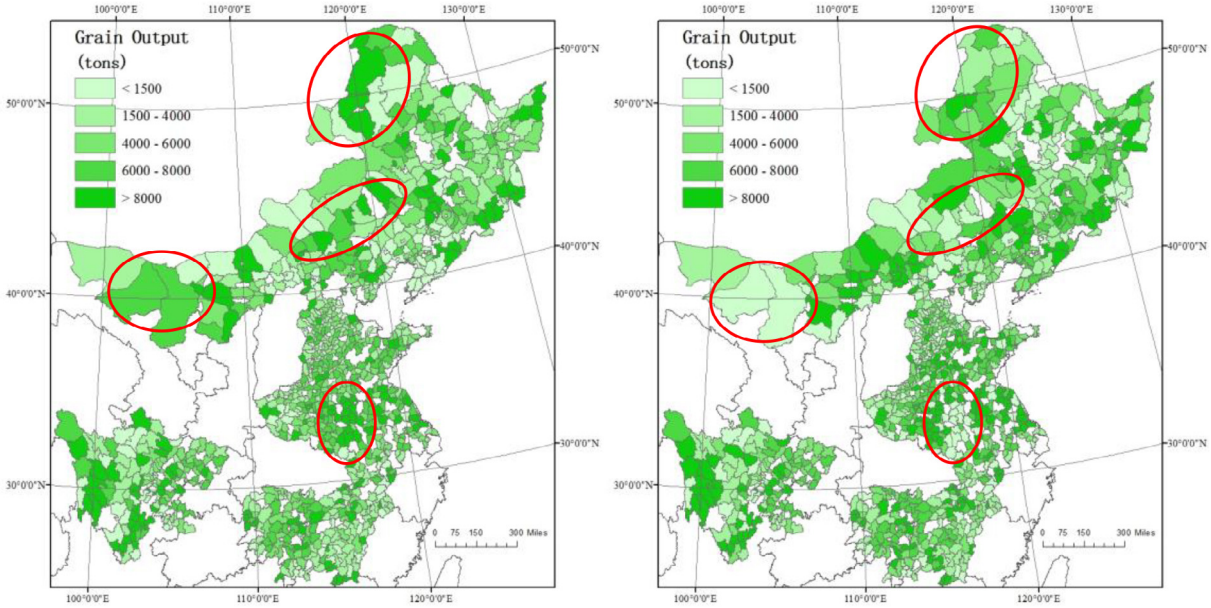

Fig. 2. Distribution map of grain production in major grain production region in 2000 and 2010.

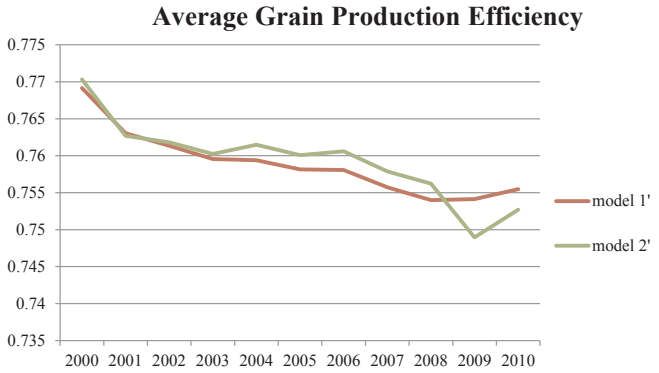

Fig. 3. Average grain production efficiency during 2000–2010 in study area.

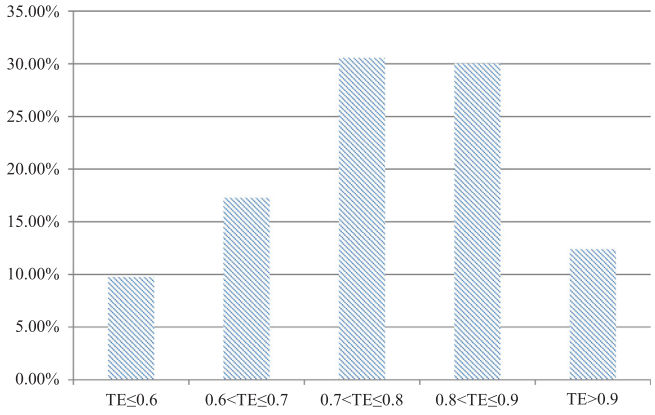

Fig. 4. Distribution of average grain production efficiency from Model 2′.

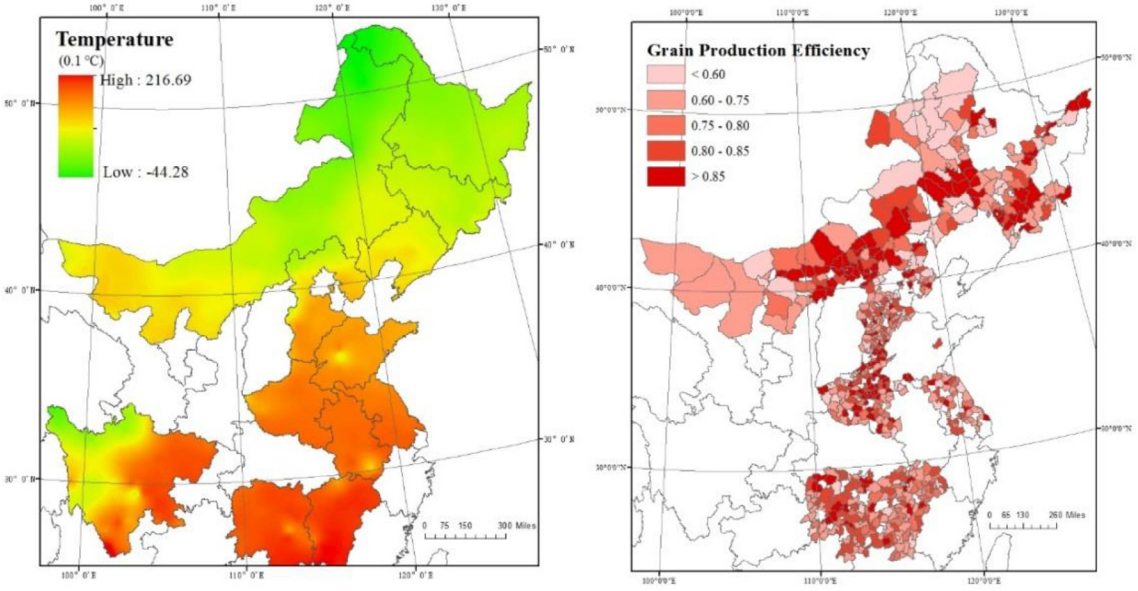

Fig. 5. Distribution of land surface temperature and grain production efficiency from Model 2′ in major grain production region in 2010.

Table 1
Data description of indicators used in input distance function.

Variable	Unit	Obs.	Mean	Std. Dev
Grain production (Y)	kg	6303	5,018,185	2,896,019
Sow area (x_1)	ha	6303	3194.04	1821.86
Agricultural labors (x_2)	person	6303	3763.9	2181.64
Agricultural machinery (x_3)	10,000*kw.h	6303	2468.26	1518.65
Fertilizer use (x_4)	ton	6303	3812.16	2214.80
Electricity for rural use (x_5)	10,000*kw.h	6303	3560.88	2020.41
Land potential productivity (x_6)	kg/ha	6303	3410.02	15253.28
Annual precipitation (*pre*)	0.1 mm	6303	8504.27	4465.88
Land surface temperature (LST) (*tem*)	0.1 °C	6303	126.56	49.39
Sunshine hour (*sun*)	0.1 h	6303	56.29	14.29
Wind speed (*fe*)	0.1 m/s	6303	21.82	5.48
Relative humidity (*ur*)	%	6303	67.49	8.89

Table 2
Results of input distance function in major grain production region.

Variables	Model 1′		Model 2′	
	Coef.	S.E.	Coef.	S.E.
Stochastic frontier estimation of input distance function				
Dependent variable: $\boldsymbol{ln}(\boldsymbol{x}_6)$				
Constant	8.05	0.31***	6.55	0.49***
$ln(Y)$	0.0036	0.045	0.0016	0.044
$ln(x_1/x_6)$	−0.85	0.066***	−0.86	0.064***
$ln(x_2/x_6)$	−0.070	0.045	−0.061	0.045
$ln(x_3/x_6)$	−0.16	0.041**	−0.16	0.040***
$ln(x_4/x_6)$	−0.11	0.036***	−0.10	0.036***
$ln(x_5/x_6)$	0.15	0.043***	0.13	0.043**
$0.5ln(x_1/x_6)^2$	−0.087	0.0033***	−0.087	0.0033***
$0.5ln(x_2/x_6)^2$	−0.087	0.0031***	−0.084	0.0031***
$0.5ln(x_3/x_6)^2$	−0.086	0.0041***	−0.087	0.0040***
$0.5ln(x_4/x_6)^2$	−0.074	0.0030***	−0.071	0.0030***
$0.5ln(x_5/x_6)^2$	−0.069	0.0032***	−0.069	0.0032***
$0.5ln(Y)^2$	0.0020	0.0032	0.0021	0.0032
$\ln(x_1/x_6)*\ln(x_2/x_6)$	0.038	0.0029***	0.038	0.0029***
$\ln(x_1/x_6)*\ln(x_3/x_6)$	0.021	0.0029***	0.022	0.0028***
$\ln(x_1/x_6)*\ln(x_4/x_6)$	0.015	0.0030***	0.015	0.0030***
$\ln(x_1/x_6)*\ln(x_5/x_6)$	0.024	0.0025***	0.024	0.0024***
$\ln(x_2/x_6)*\ln(x_3/x_6)$	0.039	0.0028***	0.038	0.0028***
$\ln(x_2/x_6)*\ln(x_4/x_6)$	0.015	0.0025***	0.014	0.0025***
$\ln(x_2/x_6)*\ln(x_5/x_6)$	0.016	0.0025***	0.016	0.0025***
$\ln(x_3/x_6)*\ln(x_4/x_6)$	0.016	0.0028***	0.016	0.0028***
$\ln(x_3/x_6)*\ln(x_5/x_6)$	0.0060	0.0026**	0.0063	0.0026**
$\ln(x_4/x_6)*\ln(x_5/x_6)$	0.033	0.0030***	0.033	0.0030***
$\ln(x_1/x_6)*\ln(Y)$	0.041	0.0042***	0.042	0.0042***
$\ln(x_2/x_6)*\ln(Y)$	−0.0059	0.0029**	−0.0062	0.0029**
$\ln(x_3/x_6)*\ln(Y)$	−0.00019	0.0026	−0.00070	0.0026
$\ln(x_4/x_6)*\ln(Y)$	−0.0020	0.0024	−0.0023	0.0024
$\ln(x_5/x_6)*\ln(Y)$	−0.018	0.0029***	−0.017	0.0029***
$ln(pre)$			0.011	0.0071
$ln(sun)$			0.065	0.043
$ln(fe)$			0.064	0.035*
$ln(ur)$			0.18	0.069***
tem			0.0037	0.00071***
$(tem)^2$			−0.000014	0.000003***

Note: *$p < 0.1$; **$0.01 < p < 0.05$; ***$p < 0.01$.

Table 3
Model test for Table 2.

Item	Model 1′	Model 2′
Log-likelihood value	862	897
Wald chi2	27782***	27900***
Gamma	0.66	0.62

Notes: if $p \leqslant 1\%$, three stars are shown for data in S.E. column of Table 2; if $1\% < p \leqslant 5\%$, there are two stars, and if $5\% < p \leqslant 10\%$, there is one star.
*$p < 0.1$; **$0.01 < p < 0.05$; ***$p < 0.01$.

Table 4
Technical inefficiency model based on Model 2′.

Variables	Coef.	S.E.
Estimates of technical inefficiency model		
Dependent variable: technical inefficiency		
$ln(x_1)$	−0.000059	0.00012
$ln(x_2)$	−0.00030	0.00010***
$ln(x_3)$	0.00039	0.00010***
$ln(x_4)$	0.00019	0.00010**
$ln(x_5)$	0.000097	0.000087
$ln(x_6)$	−0.00033	0.00015**
$ln(pre)$	0.0077	0.00041***
$ln(sun)$	−0.014	0.0013***
$ln(fe)$	−0.014	0.0012***
$ln(ur)$	0.071	0.0020***
tem	−0.00012	0.000038***
$(tem)^2$	0.0000014	0.00000016***

Note: *$p < 0.1$; **$0.01 < p < 0.05$; ***$p < 0.01$.

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